



# Resignation Calls and Dismissals of Ministers in Latin America

Notes on Data Gathering using Machine Learning

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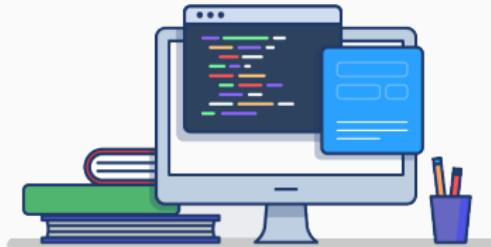
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# Tabla de contenidos

1. Introduction
2. Data Collection and Creation of the Data Set
3. Machine Learning Models to Classify Resignation Calls
4. Concluding Remarks



# Introduction

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## Theoretical Gap

The literature on coalitions in presidential systems, ministerial reshuffles, and ministerial recruitment is diverse. However, there remains a lack of clarity about the relationship and incentives between presidents and cabinet members. For example, **when is a president willing to remove a cabinet member, and when is she willing to protect him in the face of scandals, policy failures or other challenges?**

The answer lies in a number of interrelated factors, such as chains of delegation and incentives in the principal-agent relationship between the president and her ministers or between the president and the electorate (Elgie, 2020).

## Resignation Calls as Proxies

Other elements can shape the presidential decision, such as different **stochastic events** that tend to operate as random shocks affecting government stability (Chiba et al., 2015; Fortunato and Loftis, 2018), or **moral hazard** and **agency problems** that can affect cabinet performance (Chaisky et al., 2018; Martínez-Gallardo and Schleiter, 2015). Indeed, the literature has identified that protests, economic crises, scandals of different sorts, among other stochastic events, do affect cabinet stability (Camerlo and Pérez-Liñán, 2015; Martínez-Gallardo, 2014).

However, as Berlinski et al. (2010) point out, it is **complex and empirically costly** to assess all possible random shocks. Therefore, cues such as **calls for ministers to resign** may be empirically efficient indicators. This information, nevertheless, is scarce in several countries and non-existent in Latin America.

# NLP for Data Collection

This working paper presents a new data set created using **Natural Language Processing (NLP)** and **machine learning techniques**. The data set contains detailed information on the cabinet turnover in 12 Latin American democracies from the time of redemocratisation between the 1970s and 1980s, depending on the case, up until the end of the latest presidential terms.

To this end, we used a number of sources of public information and press reports that were digitised with data mining algorithms. Using machine learning models, we were able to identify ministerial resignation calls during the period. This data is indeed **completely novel for Latin American presidentialisms**.

## **Data Collection and Creation of the Data Set**

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## First Raw Data Set

Data collection is based on a three-stage procedure. First, a **raw data set of ministers and portfolios** is compiled according to a number of relevant variables (*i.e.*, country, name of the minister, gender, party affiliation, appointment date, etc.)

This raw data set is compiled from a revision of official sources, recognised press, the information available in the libraries of Congress of each country, and data from the **Latin America Weekly Report (LAWR)**.

These weekly reports of between 12 and 16 pages long present a compendium of relevant news on each country in the region. On average, they constitute approximately 600 pages per year until 2002 and 800 pages since then. These reports are a significant source of aggregate information at a regional level.

## First Raw Data Set

Second, a **novel raw data set of weekly ministerial resignation calls** is generated from a revision of media reports from LAWR. For this, the specific mentions of cabinet members are identified, allowing us to identify and codify the variable of resignation calls. To this end, LAWR archives were compiled in three different batches of data.

These files are stored in a private repository with a version control system on  GitHub whose access is controlled by  Two-Factor Authentication (2FA). In addition, it is backed up on  Hierarchical File Server (HFS) for recovery in case of unforeseen incidents on the University of Oxford hub connected to Code42 Cloud Backup GUI-based, allowing version control, restoration, and automatically scheduled backups, and 256-bit Advanced Encryption Standard (AES).

# Detail of the Batches of the LAWR Archives

Batch	Archives	Years	Format	Volume
Batch-01	LAWR-1975 to LAWR-1979 Including 1997	5	CSV UTF-8	9.56 MB
Batch-02	LAWR-1980 to LAWR-1998 Excluding 1997 Including the first half of 2003	18.5	PNG images	38.5 GB
Batch-03	LAWR-1999 to LAWR-2021 Excluding the first half of 2003	22.5	PDF files	341 MB

Note: Revision of 12 Latin American countries thanks to St Hilda's College Muriel Wise Fund and subscriptions of the Bodleian Libraries at the University of Oxford.

## Binarisation Algorithms

Note: Images correspond to a LAWR page before binarisation and after the application of techniques of Sauvola and Pietikäinen (2000) and Su et al. (2010).

## Tesseract OCR Algorithm



### **How Domingo Cavallo rose to become Menem's virtual prime minister**

Argentines are still highly debating what led behind the sudden resignation of economy minister Antonio Ermelo Gómez-Pompa and his replacement by Martín Redrado as central bank chief. The simple explanation — the most uncontested usage of the so-called “tango” — is considered as suffic-  
ient by many analysts, who have published about all sorts of political plots.

One thing seems certain: that Gómez-Pompa never intended to resign at Mervar — according to sources with access to him, he had planned to remain until President Fernando de la Rúa's term ended in December 2001. Indeed, a widely accepted version is that Mervar had always intended to resign, but that he was forced to do so, at precisely the time of his reactivation — which he expected would take a first phase of “stable inflation.” In other words, as Gómez-Pompa did not want to choose his own timing,

It was at this point, the scenario goes, that Carlos' behavior—Menem's resolve to hang on, as it was—caused Casella to emerged not only as the new economy messenger but as a virtual prima ministra. He organized a series of key meetings with men in order to support his own people in other ministries. Casella, it is said, has replaced even Senator Eduardo Menem, the President's brother, as Carlos Menem's most trusted adviser.

**PETRO:** "Widespread spread of cholera epidemic, (in)  
**EQUADOR:** "Today" Reduces Impact on HIRALDO  
**COLUMBIA:** Prospects of viral disease, with CHOLERA

**EL SALVADOR:** Setback  
as FMLN "resumes  
negotiations," (10/1/11)  
  
**COSTA RICA:** Preparing a  
new just-in-time, (11/11)  
  
**PANAMA:** Time to recall  
Hartog offices? (11/11)



## How Domingo Cavallo rose to become Menem's virtual prime minister

Opponents were still holding out, but by the beginning of November, the president had won over most of the Senate. Even Gonzalez and his relatives, who had been instrumental in the simple explanation—the one that got the most support—had come around. It was a remarkable rate—“dramatic” is how Gonzalez put it—and it was something he had not even imagined about all sorts of politics.

One thing remained: the House. His third secretary of defense, Robert Gates, had told him that he had “President Clinton’s support.” But when Gonzalez asked him, a widely respected conservative, if he would support the president’s proposal to expand gays as his secretary of defense, Gates responded with a question: “What do you expect?” which he expected him to say no. In a few short days, though, he had changed his mind. “I was shocked,” he said. “I was shocked to find myself in agreement with him.”

Another strand of interpretation is that the change took place because of the president’s political alliance with the military, which had been strengthened by the depth of popular feeling over the war in Iraq. The president’s support for the military leaders of the war was seen as a way to keep them on board for the administration’s long-term strategy in the region. And the president’s decision to withdraw from the Bush administration that decision that he had made in 2001 was seen as a way to gain their passing support from the Bush administration.

This, at a time when even some of the president’s closest supporters, like Robert Gibbs, the president’s chief of staff, and David Frum, the president’s speechwriter, were calling for the administration to apologize to America’s gay community, was a remarkable achievement. It was also a remarkable achievement for the president himself. He had been the one who had been the most vocal about the importance of the military in the president’s policies. He would not have been able to do what he did without the support of the military.

INFOGRAPHIC	
PERU: Wildfires spread of Peters epidemic, CT	VENEZUELA: Lowest prices since budget re-think
TAIWAN: 'Paradise' miners' impact on HK	SOLVIM: Soviet partner for new lithium scheme? D)
COLombIA: Prospects of TUM, abroad, with CMC	PARASITE: Another in PC
	PRISON: Update and the 'Sull' affair, Texas, US
	GRIAL: Few months for Philip Morris R, if it is
	CHEL: Proposal to extend Afghan's mandate
	HATT: Attributed to first major challenges



### **How Domingo Cavallo rose to become Menem's virtual prime minister**

**Argentina** is still fully dedicated why it became the leading success story in Latin America. President Ernesto González and his replacement, Fernando de la Rúa, have both been instrumental in this success. The simple explanation – as the former president himself has pointed out – is that Argentina's economy has been transformed from a state-controlled, centrally planned economy to a market-oriented, privately owned and all sorts of political correctness.

The one remaining concern that I have about Argentina is that its foreign reserves remain at a very low level. In my view, this is due to the fact that President Fernando de la Rúa, a widely admired economic liberal, has been unable to convince Congress that the economy needs to be further liberalized. He has explained that he expected more funds to flow into Argentina if he were to choose his own timing.

Another sound argument is that the change took place as a result of the political changes, triggered by a series of elections, which have led to the decline of apparently popular left-wing parties such as the Peronists and the military leaders of the 'Dirty War'. The new government has been welcomed enthusiastically in the United States, where there is a strong demand for investment from Argentina. This is despite the general pessimism expressed by the Bush administration.

The US is a little behind the Argentinean government in its support for President Fernando de la Rúa. The main reason for this is that the leadership is regarded as being too conservative in its approach to the economy. It is also worth noting that the US has been critical of the procedures adopted since the recent

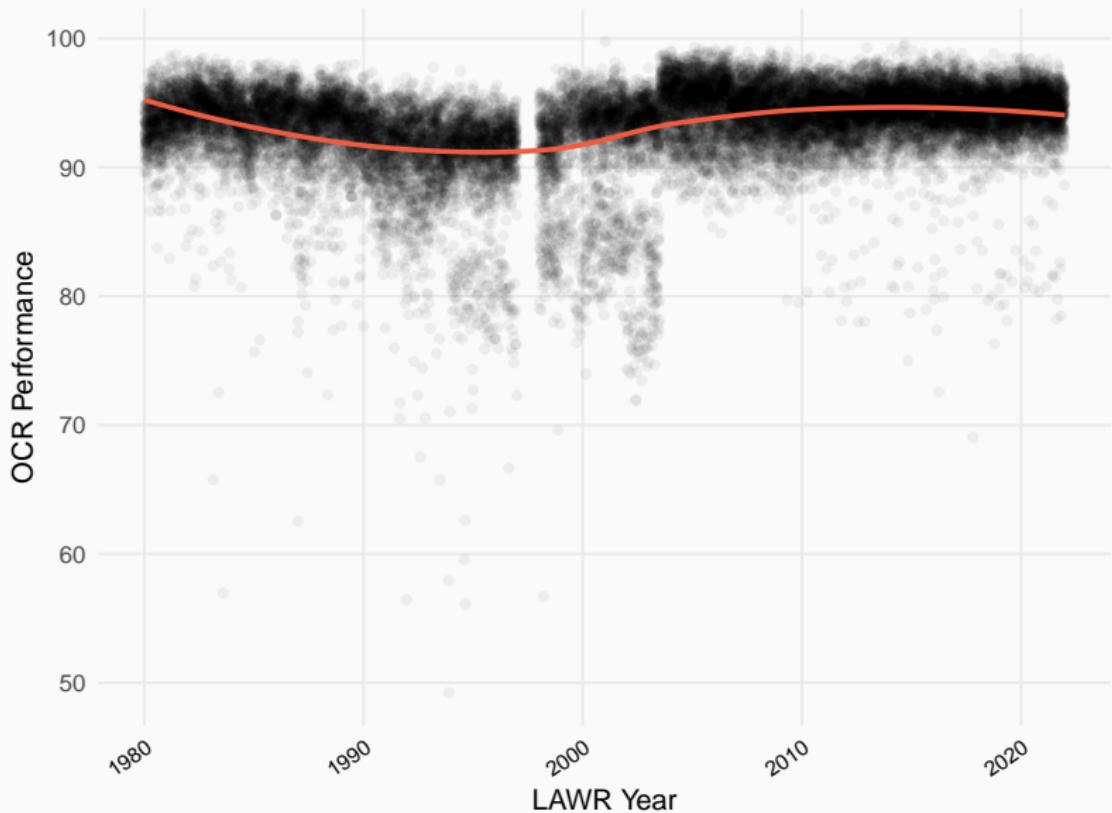
## Year and Week

## Headline

### Paragraph

## Tab-Stop Lines — Column Layout — Segmented Blocks

# Accuracy of the OCR Algorithm



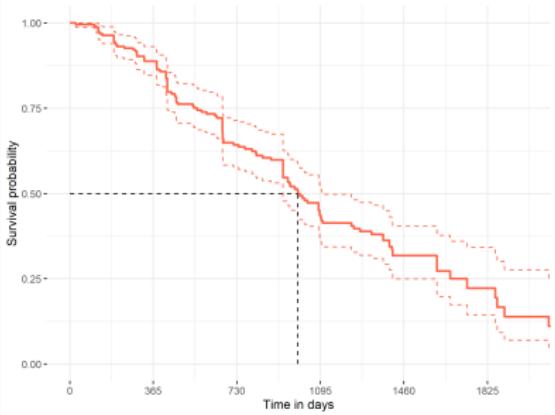
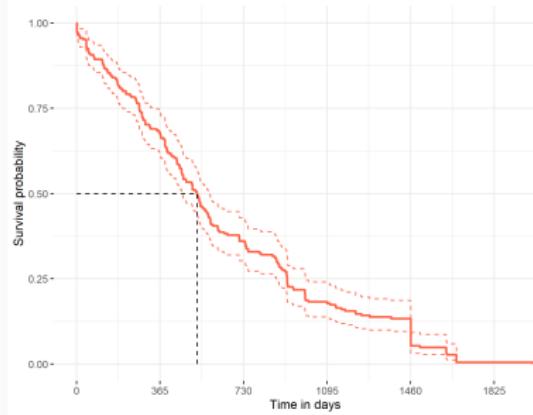
# Data Structure

- ❶ OCR application on **41 years** of files with a total of **28,090 pages**.
- ❷ We identified **18,198 mentions** of ministers and cabinets members (incorporating the first batch this increases to **19,925** and the coverage to **46 years**).

We elaborate a weekly data set with resignation calls to merge with the first raw data and other sources such as approval, party systems variables, and macroeconomic indicators.

Therefore, we encode the data as **time-dependent** covariates accounting for changes over time.

# Examples of Kaplan-Meier Survival Estimations



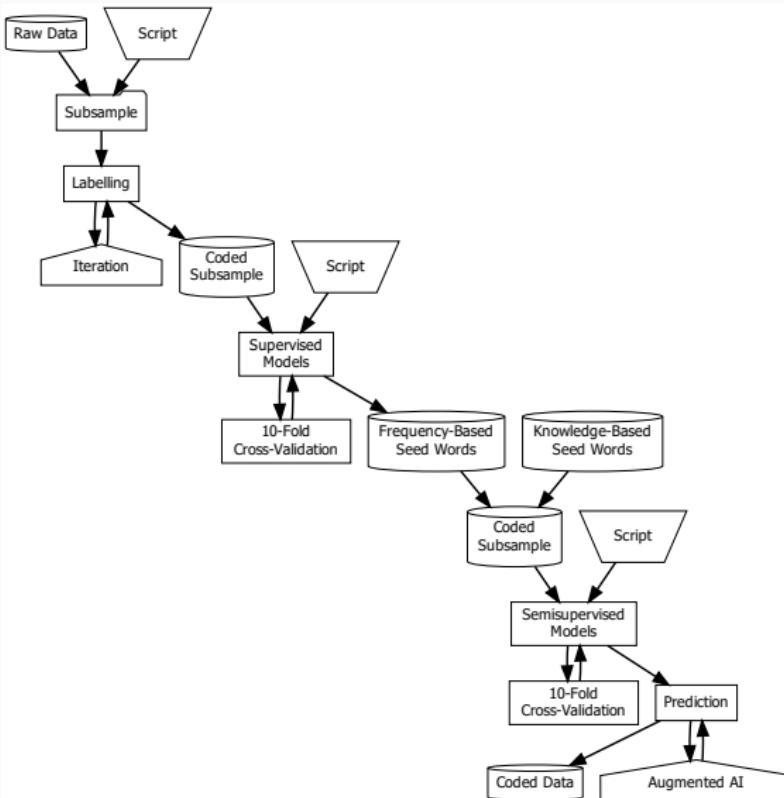
Note: The plots show Argentina and Chile with a 95% confidence interval and median survival.

**How do we distinguish between mentions and calls?**

# **Machine Learning Models to Classify Resignation Calls**

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# Machine Learning Algorithms Training Pipeline



# Labelling for Training Supervised Models

- ❶ Random subsample of **1,000 LAWR press releases** considering cabinet mentions. Assets pool of 3,000 observations (three hand-coded labels per unique report).
- ❷ We use the online labelling platform  [Labelbox \(2021\)](#), which subsequently allows all the information to be exported in JavaScript Object Notation (JSON) format for processing.

The labelling was conducted by **six human coders**, involving 41 hours and 55 minutes of actual work on the platform using [Dewan and Dowding's \(2005\)](#) categorisation: personal scandals, financial scandals, policy failures, internal disagreements, or other controversies.

# Performance of the Labelling Process

Coder	Labels	$M(T)$ Label	$\sum$ Time	Consensus
1	966	39s	10h 25m	94.05
2	718	1m 15s	15h 0m	94.84
3	704	38s	7h 29m	94.82
4	318	1m 4s	5h 38m	95.47
5	263	17s	1h 14m	99.26
6	101	1m 17s	2h 9m	88.50

Note: Krippendorff's  $\alpha$  (bootstrap of 1,000 iterations) = 0.870 and CI<sub>95%</sub>: 0.844 to 0.900.

Considering a binary classification of resignation calls  $\alpha$  = 0.895 and CI<sub>95%</sub>: 0.868 to 0.922.

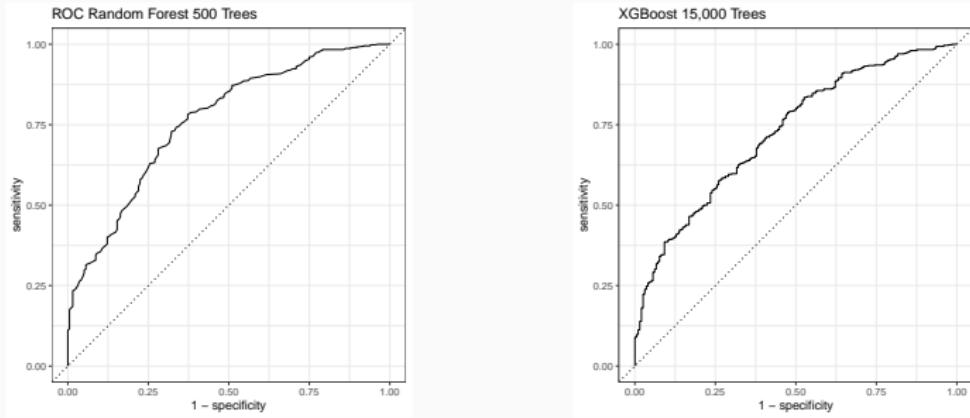
# Performance of the Supervised Classifiers

Model	Snowball 500 Tokens		
	Accuracy	Precision	Recall
Naïve Bayes	0.714	0.803	0.825
Kernel Linear SVM	0.658	0.802	0.728
Kernel Gaussian RBF SVM	0.756	0.756	0.999
Random Forest (100 trees)	0.761	0.760	0.998
Random Forest (500 trees)	0.761	0.760	0.999
XGBoost	0.784	0.811	0.932

Model	Stemming SMART 100 Tokens		
	Accuracy	Precision	Recall
Naïve Bayes	0.725	0.786	0.876
Kernel Linear SVM	0.735	0.785	0.894
Kernel Gaussian RBF SVM	0.766	0.766	0.993
Random Forest (100 trees)	0.775	0.773	0.995
Random Forest (500 trees)	0.771	0.770	0.995
XGBoost	0.771	0.809	0.912

# ROC Curve for Random Forest and XGBoost



# Performance of the Semisupervised Classifiers

Model	Knowledge-Based Seed Words		
	Accuracy	Precision	Recall
Naïve Bayes	0.713	0.734	0.948
Kernel Linear SVM	0.698	0.741	0.900
Kernel Gaussian RBF SVM	0.726	0.728	0.995
Random Forest (100 trees)	0.743	0.742	0.991
Random Forest (500 trees)	0.743	0.740	0.997
XGBoost	0.726	0.762	0.905

Model	Frequency-Based Seed Words		
	Accuracy	Precision	Recall
Naïve Bayes	0.758	0.805	0.918
Kernel Linear SVM	0.771	0.808	0.932
Kernel Gaussian RBF SVM	0.793	0.794	0.997
Random Forest (100 trees)	0.799	0.797	0.999
Random Forest (500 trees)	0.801	0.799	0.999
XGBoost	0.794	0.819	0.948

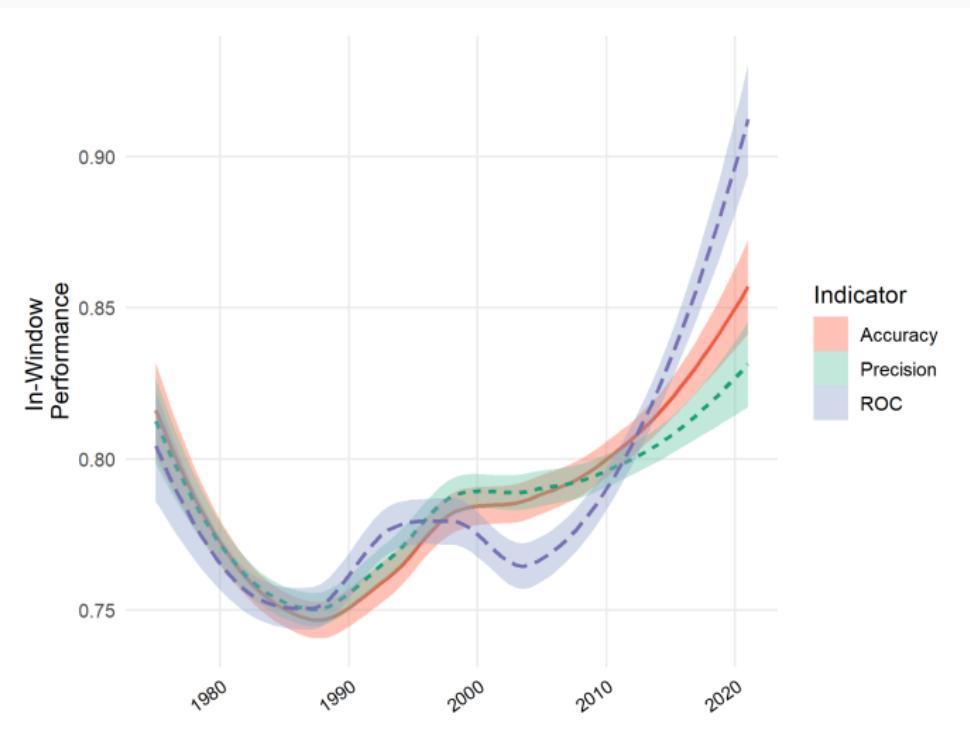
# Seed Words and Fixed Rolling Windows

- ❶ If we consider both seed words sets, the level of agreement between machine and human labelling, considering our subsample coded on Labelbox (2021), is 69.2% for machine and two human coders.

We follow a strategy similar to that used by [Greene et al. \(2019\)](#): **Five-years fixed rolling window** between 1975 and 2021 to train our models and predict resignation calls.

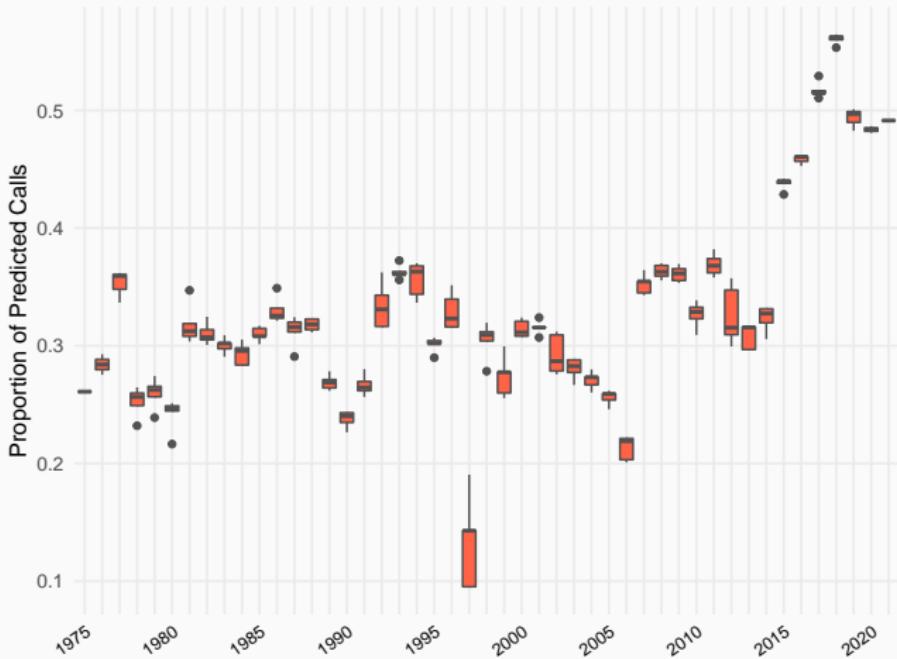
Therefore, the first window covers the period from 1975 to 1979, the second between 1976 and 1980, and successively until the forty-third window from 2017 to 2021.

# Performance of the Semisupervised Models (1975-2021)



Note: Indicators 10-fold cross-validated in the five-years rolling window.

# Predicted Ministerial Resignation Calls (1975-2021)



Note: Predictions proportion over the mentions carried out with the ensemble semisupervised Random Forest (500 trees) in the five-year rolling window.

## Concluding Remarks

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# Concluding Remarks

This working paper presented a pioneering application of OCR procedures and machine learning models to build a data set with **novel information** on cabinet members' calls for resignation in **12 Latin American democracies**. This can help study coalition dynamics in presidential systems, cabinet management and stability, political recruitment processes at the ministerial level, etc.

This is still a **work in progress**. Further work on distinguishing resignation calls in more detail is necessary. In addition, the data set needs to be contrasted with other similar sets.

Our data set permits the outlining of empirical strategies with and without causal identification strategies to estimate different types of nonparametric and parametric econometric models, as well as competing risks and survival analysis approaches.

## Acknowledgements and Data Sharing

## Acknowledgements

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Finally, thanks to the human coders who conducted the labelling process to train the supervised models.

## Preservation and Data Sharing

The data set will be deposited in the digital repository  Oxford Research Archive for Data (ORA-Data) in  CSV UTF-8 format with its codebook and standardised metadata. The data set will remain under embargo until October 2023 (to be confirmed).

It will then be available for reuse under an  open-access licence that allows sharing and adapting the material without additional restrictions as long as appropriate acknowledgement is given.

Further technical details on storage, formats and replicability are available in the Data Management Plan (DMP ID 85349).

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Thank you very much!

